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THE BIOGRAPHY OF AN ALGORITHM:

PERFORMING ALGORITHMIC TECHNOLOGIES IN ORGANIZATIONS

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ABSTRACT

Algorithms are ubiquitous in modern organizations. Typically, researchers have viewed algorithms as self-contained computational tools that either magnify organizational capabilities or generate unintended negative consequences. To overcome this limited understanding of algorithms as stable entities, we propose two moves. The first entails building on a performative perspective to theorize algorithms as entangled, relational, emergent, and nested assemblages that use theories—and the sociomaterial networks they invoke—to automate decisions, enact roles and expertise, and perform calculations. The second move entails building on our dynamic perspective on algorithms to theorize how algorithms evolve as they move across contexts and over time. To this end, we introduce a biographical perspective on algorithms which traces their evolution by focusing on key "biographical moments." We conclude by discussing how our performativity-inspired biographical perspective on algorithms can help management and organization scholars better understand organizational decision-making, the spread of technologies and their logics, and the dynamics of practices and routines.

INTRODUCTION

Algorithmic (including AI and data-driven) technologies have become increasingly central concerns for organizations and organization theorists. Organizations use algorithms—"precise recipes that specify the exact sequence of steps required to solve a problem"—to augment and automate a variety of organizational practices or routines ranging from recommending media content to automatically recognizing entities, assessing security risks, optimizing logistical efficiency, or evaluating the desirability of individuals who are applying for credit or coming up for parole (MacCormick, 2012, p. 2). Such algorithms are now fundamental features of contemporary organizing, enabling organizations to process the "vast, fast, disparate, and digital" data produced in contemporary social and organizational life (Brayne, 2017, p. 980). The pervasive influence of algorithmic phenomena means that the "majority of manufacturing processes, the organization of services to 'citizen' and 'customer,' and the myriad of 'clicks' that regulate our daily lives, are all inspired by algorithmic models" (Totaro & Ninno, 2014, p. 30). Due to their profound consequences, scholars have argued that it is imperative to develop theory that enables a better understanding of how algorithmic technologies can "alter work and organizational realities" (Faraj, Pachidi, & Sayegh, 2018, p. 67).

In organizational research on the effects of algorithmic technologies, researchers have focused on two potential and contrasting outcomes. Some scholars have highlighted the potential of algorithmic tools to provide organizations with affordances that facilitate value creation by making better predictions (Mayer-Schönberger & Cukier, 2013), automating structured and repetitive work (Davenport, 2018; Steiner, 2012), reshaping organizational culture (Fountaine, McCarthy, & Saleh, 2019; Schildt, 2020), and improving the flow of ideas between distinct social domains (Pentland, 2014). Other scholars have focused on the dark side of these technologies, including how they enable management to control workers (Kellogg, Valentine, & Christin, 2019), establish formal and inflexible rules that strip away more nuanced, values-based means of working through social challenges (Lindebaum, Vesa, & den Hond, 2019), and provide corporations with the ability to generate socially consequential rankings based on obfuscated algorithms (Martin, 2019; Pasquale, 2015) that manipulate individuals (Yeung, 2017) in ways that possibly undermine their rights (e.g., privacy, autonomy) (Noble, 2018) in exchange for convenience and efficiency (Zuboff, 2019).

Although prior research captures the broad influence of algorithmic technologies on organizations, scholars have developed a limited conception of these technologies that highlights either their extreme benefits or costs. By relying on a narrow understanding of algorithms as discrete and opaque computational tools, these accounts have not done enough to expand our ability to theorize the generative and diverse possibilities algorithmic technologies afford organizations (e.g., Raisch & Krakowski, in press; von Krogh, 2018). This risks preventing us from understanding and capturing the complex and often invisible (albeit often powerful) influence of algorithmic technologies on organizations and organizing.

To overcome this limitation, we posit that algorithms can be more productively analyzed by employing a framework that recognizes their inherently "contexted" nature (e.g., Bailey & Barley, 2019; Callon, 1998; D'Adderio, 2008; Mol, 2002; Orlikowski & Scott, 2008, 2016). In this paper, we set out to do so by drawing on performativity theory (e.g., Callon, 1998; D'Adderio, Glaser, & Pollock, 2019) and assemblage theory (e.g., DeLanda, 2016; Deleuze & Guattari, 1987) to conceptualize algorithms in terms of their entanglement in sociomaterial assemblages. Rather than focus on algorithms as discrete entities, analyzing algorithms as assemblages enables us to understand how theories are used to automate decisions, enact roles and expertise, and perform sociomaterial calculations. Moreover, senstitized by a biographical perspective (e.g., Hyysalo, Pollock, & Williams, 2019; Pollock & Williams, 2009), we introduce a framework for studying the evolution of algorithmic assemblages from a dynamic and contextualized perspective: the *biography of an algorithm.* In so doing, we highlight three possible pivotal moments in this biography: addressing and resolving performative struggles, inscribing and layering programs of action, and translating algorithms to other contexts.

By combining a performative and a biographical framing, we develop a more appropriate and useful theorization of algorithms that acknowledges their entangled, complex, and dynamic agency and their assemblages. Specifically, our approach provides a more nuanced and powerful understanding of how algorithms are reshaping organizational life while enabling deeper explanations of the nature of algorithms and their effects. Specifically, we generate novel theory about the influence of algorithmic technologies on a range of organizational topics, including: processes of organizational decision-making; the spread of theories and technologies and their logics; and the dynamics of organizational practices and routines.

ALGORITHMS AS COMPUTATIONAL TOOLS

Existing organizational and social science research has often relied on a narrow "computational" view of algorithms as a type of technology with the capability "to represent, manipulate, store, retrieve, and transmit information, thereby supporting, processing, modeling, or simulating aspects of the world" (Orlikowski & Iacono, 2001, p. 127). The computational view of the algorithm, based on a limited technical perspective, has often treated algorithms as essentially self-standing, autonomous and "black-boxed" entities whose properties and effects are independent from their design and application contexts. From a strictly computational and programming perspective, an algorithm involves two main components: the "logic" component, which defines what needs to be done (e.g., the abstract formulation of a solution), and the "control" component, which defines how it should be done (e.g., the problem-solving strategy of choice and instructions for processing the logic under different scenarios) (Gillespie, 2014; Kitchin, 2017; Kowalski, 1979). In turn, these steps require two translations: (a) the translation of a task or problem into a structured formula and related rule set (known as the "pseudo-code"), and (b) the translation of the pseudo-code into source code that, once compiled, will perform the task or solve the problem (Gillespie, 2014).

In this prevailing computational view, the two processes of translation are understood to be "strictly rational concerns, marrying the certainties of mathematics with the objectivity of technology" (Seaver, 2019, p. 412). Typically performed by computer programmers, technology users, and producer organizations, such translations are viewed as "technical, benign, and commonsensical" (Kitchin, 2017, p. 17)—a characterization which leaves the messier (but fundamental) aspects of algorithmic production and use and the more complex organizational, institutional, processual, and material dynamics of algorithms (Gillespie, 2014) almost entirely out of the picture. In this respect, a computational construction tends to "black box" algorithms, which are described as stable and settled artifacts that are presumed to work and perform as their designers intended (Pasquale, 2015).

Thus far, this objectified computational tool perspective has been the dominant perspective in management research. For instance, Kellogg et al. (2019) highlighted how algorithms are used by management to direct, evaluate, and discipline workers. Algorithms thus direct workers to make decisions preferred by a choice architect and to recommend specific courses of action, which can lead to feelings of frustration or perceptions of bias (Kellogg et al., 2019). Similarly, Curchod, Patriotta, Cohen, and Neysen (2020) suggested that algorithms reproduce power asymmetries among different categories of actors in contexts associated with online evaluation. Their research shows that algorithms, as intermediating and black-boxed tools, enable and constrain human agency in important ways—including generating new forms of employee monitoring, mediating across different categories of actors, and enabling actors to increase their power (e.g., Murray, Rhymer, & Sirmon, in press). Management researchers have thus essentially viewed algorithms as being "supercarriers" of formal rationality (Lindebaum et al., 2019) that provide organizational actors with the ability to dramatically transform organizational processes (Schildt, 2020). Put simply, by viewing algorithms as computational tools, algorithms become a means to further a Taylor-like rationalization of organizational processes (Petriglieri, 2020), which might lead to partial or, in some cases, even simplistic insights over their effects.

Limitations of the Algorithms as Computational Tools Perspective

The view of algorithms as computational tools has three issues that limit our ability to develop a fully formed theoretical account of algorithms and organizations. First, from the computational tool perspective, algorithms are typically viewed as independent entities often endowed with strong talismanic properties. For example, according to Lash (2007, p. 71) power is seen as increasingly delegated to or found "in the algorithm" in a manner that makes algorithms seem all-powerful. Similarly, Galloway (2012, p. 92) pointed to how we live in an "age of algorithms" and that "power today resides in networks, computers, algorithms, information, and data." These theoretical assumptions appear to closely reflect the rhetorical claims advanced by technology producers whereby algorithms are seen as direct causes of radical social and organizational transformation or upheaval. In their account of the "age of the algorithm," for instance, industry analyst firm Forrester highlighted how organizational decision-making is now very much in the hands of algorithms (e.g., Khatibloo, 2018). By reifying the technology and its properties, however, these academic and practitioner narratives prevent us from ascertaining and understanding the implications of algorithms.

Second, the computational tool view tends to overlook the wider socio-technical character of the translations involved in the organizational use of algorithms. A broader, rather than narrowly understood conception of algorithms shows how—far from being the result of one-off technical exercises—these technologies are shaped as they are enacted, through their progressive entanglement with a diverse range of material and non-material actants (Gillespie, 2014, 2016). Algorithms thus evolve by being typically activated through a chain of socio-technical translations (Callon, 1986; Latour, 2005) or "chain of materializations" (D'Adderio & Pollock, 2020) that are required to translate the algorithmic logic and code into organizational activity. One materialization, for example, might convert an abstract logic into a mathematical model or formula. Another materialization might involve translating this formula into code which can be executed by a machine (e.g., a computer). A further materialization might concern translating this code in the form of software scripts so that it can be embedded into a software application. Yet another materialization might involve the software application being adopted and becoming embedded in new and different organizational and institutional contexts. Put simply, this progressive (and/or simultaneous) chain of materializations enables the original algorithm constructed in a narrow way (logic plus code) to come to life and be transported through many different—and often unpredictable—instantiations.

Third, the computational tool view overlooks the contextual organizational, environmental, and institutional features dynamically contributing to shaping algorithms across space and over time, including customs, culture, knowledge, or resources (e.g., Porter, 1996);

global instruments such as regulatory frameworks, classifications, standards, policies, or the law (Mennicken & Espeland, 2019; Yeung, 2018); decision-making and problem-solving characteristics such as expertise, choice, and judgment (Aversa, Doherty, & Hernandez, 2018; Galliers, Newell, Shanks, & Topi, 2017); and material contingencies such as hardware, platforms, or languages (Nambisan, Wright, & Feldman, 2019). As created and enacted within a thick web of proximities and relationalities, algorithms thus stretch far beyond both the narrow conditions under which they are developed and deployed, and purely technical domains (Geiger, 2014). If and when algorithms act, "they do so as part of an ill-defined network of actions upon actions" (Goffey, 2008, p. 19). Actions in and around the algorithm thus belong to "people debating the models, cleaning the training data, designing the algorithms, tuning the parameters, deciding … which algorithms to depend on in which context" (Gillespie, 2016, p. 22). This points to the intrinsic limitations of studies focused on algorithms as "islands of automation," as highlighted by Pollock and Williams (2009). Algorithmic applications therefore are not "standalone little boxes, but massive, networked ones with hundreds of hands reaching into them, tweaking and tuning, swapping out parts and experimenting with new arrangements" (Seaver, 2019, p. 419). They are also often part-and-parcel of more integrated organizational offerings that are not governed by a single coded logic, because in practice, organizations use multiple algorithms simultaneously (Neyland, 2016).

A PERFORMATIVE PERSPECTIVE ON ALGORITHMS

These limitations in the current understanding of the role of algorithms (and related digital technologies) for organizing have been acknowledged in some recent contributions drawing on the notion of performativity (e.g., D'Adderio et al., 2019; Garud & Gehman, 2019; Garud, Gehman, & Tharchen, 2018; Gond, Cabantous, Harding, & Learmonth, 2016).

Performative perspectives on organizing highlight the ways in which words *create* and influence social reality, rather than merely *describe* social reality (Austen, 1962). For instance, from an economics perspective, individuals are framed as behaving in a self-interested manner; however, this framing may not simply describe an existing reality, but actively engender a new reality (Ferraro, Pfeffer, & Sutton, 2005). Rather than conceptualize agency as residing in specific people or artifacts, a performative perspective highlights the seamlessly interconnected nature of assemblages[1] (e.g., Callon, 1998; Carton, 2020; D'Adderio, 2008, 2011; Deleuze & Guattari, 1987; MacKenzie, 2006; Orlikowski & Scott, 2008; Suchman, 2007), the set of "heterogeneous elements that is required for the world contained in [a performative] statement to be actualised" (MacKenzie, 2003 in D'Adderio, 2008, p. 776).

This means that, in practice, enacting and materializing an algorithm's rules and assumptions requires an assemblage consisting of deeply entangled components to be produced and reproduced (D'Adderio, 2008; D'Adderio & Pollock, 2014). A performative perspective thus suggests that, rather than viewing an algorithm (or indeed any technology) as a self-standing and independent entity, we must account for all of the inherently relational and distributed sociomaterial features which contribute to its making and remaking, such as humans, artifacts, theories, etc. (D'Adderio, 2008, 2011; D'Adderio et al., 2019; Glaser, 2017). When an assemblage is enacted, it can be described in terms of a performation (Callon, 2007). A performative perspective thus highlights the importance of analyzing social phenomena in terms of an assemblage, rather than separate "actors" or "actants" who generate change through direct, intentional action. Assemblages are "arrangements endowed with the capacity to act in different ways, depending on their configuration" (Çalışkan & Callon, 2010, p. 9)—with different

[1] For simplicity, we use the term assemblage rather than the original French term *agencement* (Callon, 1998); however, we attribute to the assemblage the same characteristics and conceptualization of the agencement.

assemblage configurations bearing different effects that enable the theorization of the varying effects of statements, goals, and theories on practices (Gehman, Sharma, & Beveridge, 2020). Assemblages thus can be more or less successful in constituting the world around them (DeLanda, 2016).

The assemblage concept in performativity, we posit, can help address some of the limitations of the computational tool perspective by acknowledging the relational, distributed, and sociomaterial nature of algorithms, thereby avoiding the pitfall of treating them as self-standing and independent entities (D'Adderio, 2008, 2011; D'Adderio et al., 2019; Glaser, 2017). A performative perspective has begun to provide some insights for our understanding of algorithms in the sociology of finance, routine dynamics research, and information systems research.

Performativity, Algorithms, and the Sociology of Finance

Building on actor network theory (e.g., Callon, 1998; Latour, 1987), scholars have adopted a sociology of finance lens to understand financial markets, in particular attempting to capture the relationship between economic theories and market activities. Callon and Muniesa (2005) highlighted that one of the core functions of a market is connecting calculative agents who need to agree on a price for a good in order to engage in a transaction. They suggested that this requires "algorithmic configurations" that "calculate encounters differently, depending on how algorithms perform these operations; each concrete market corresponds to a particular mode of organization (and calculation) of the connection between singular supplies and demands" (p. 1242). Because algorithms are embedded in configurations, it is the configuration that makes a difference, not the independent algorithm.

Similarly, MacKenzie's (2006) canonical study of the performativity of finance theory empirically shows how the Black-Scholes-Merton model utilizes algorithms within the formula itself (MacKenzie & Millo, 2003, p. 131) and in various trading applications (Beunza, 2019). Interestingly, the relational enactment of the formula and its associated algorithms does not necessarily bring its world into reality. MacKenzie (2006) revealed the existence of different kinds of performativity, ranging from generic performativity (e.g., the model is used) to effective performativity (e.g., the model is used and makes a difference) to Barnesian performativity (e.g., the use of the model makes the model more "true"), or even to counterperformativity (e.g., the use of the model makes the model less true). Building on this, Beunza (2019) showed how the performative enactment of a model changes the assemblage through a process he described as a "performative spiral." This process unfolds as a functioning entangled assemblage is later challenged by processes of competition which stimulate imitation and improvement, eventually leading to the introduction of new models and assemblages.

Performativity, Algorithms, and Routine Dynamics

Authors in the field of routines dynamics have also drawn on performativity theory to begin to unravel the complex effects of algorithms and related technologies on routines and organizations (D'Adderio, 2008; D'Adderio et al., 2019). In the routine dynamics literature, procedures, software scripts, and algorithms are conceptualized as artifacts that fit within a broader assemblage (e.g., including bodies, theories, texts, objects, etc.) and whose properties emerge in practice (D'Adderio, 2008; Glaser, 2017; Glaser, Valadao, & Hannigan, forthcoming). For example, a computer-embedded script, which acts as the material instantiation of an abstract product development procedure, performs as a process theory that frames routines by bringing together a variety of material and non-material features of context into a socio-technical assemblage (D'Adderio, 2008).

D'Adderio's (2008) performativity framework articulates the degrees of influence of artifacts over routines—that is, the range of possible performative outcomes between the theoretical extremes of "description," or straightforward rejection of the artifact (e.g., a disused or rejected software package), and "prescription" or the mechanical performation of the artifact (i.e., algorithmic code being mindlessly performed by a machine without human intervention). This research shows how technologies such as standard operating procedures, software code or scripts, and algorithms inscribe the assumptions and goals of users and designers, and consequently shape and are shaped by practices and organizations with different degrees of effectiveness, ranging from weak to strong performativity. Routine dynamics research thus breaks down the unhelpful analytical separation between technology and human agency to focus on their co-performation. The power of the artifact here is described as its ability to put together an assemblage of socio-technical or sociomaterial features which supports the realization of logics, goals, and intentions embedded over time in the artifact itself (D'Adderio, 2011).

This work suggests that understanding how routines shape algorithms requires focusing on the range of actants involved in performing the routine, including the range of actors who design and enact the algorithm (Glaser, 2017) and the artifacts encoding the intentions of those very organizational agencies (D'Adderio, 2008). This highlights a second key affordance of the performativity framework: it can help us identify how intentionality may be enacted by organizational actors and encoded in artifacts, thereby influencing (albeit never fully specifying) the direction of performation and its effects, which can indeed be reverse effects as in MacKenzie's (2006) aforementioned counter-performativity. Artifacts thus exert agency through assemblages, with differential effects on routine performance (Aroles & McLean, 2016; Sele & Grand, 2016).

Performativity, Algorithms, and Information Systems Research

Information systems scholars have also discussed the co-constitution of artifacts and practices. In theorizing technology as the outcome of sociomaterial enactment, Orlikowski and Scott (2008, 2014) cautioned against the fallacy of relegating materiality to a mere mediating or supporting feature of some pre-existing practice; materiality instead is actively constitutive of practices and their outcomes. Taking issue with the idea of pre-existing categories such as "subject" and "object," "human" and "nonhuman," "matter" and "meaning," they instead framed these as enacted in practice through actual "doings" and "actions" (Barad, 2007). Materiality, they argued, is not an inherent fixed or objective property of an artifact, but a process of materialization that configures (creates) reality. Sociomateriality means that the properties and effects of objects, actors, rules, etc. are not antecedents, but outcomes of their performation in and through practices. Orlikowski and Scott (2016, p. 89) took this further by highlighting how, in order to understand digital innovations and their implications, we need to explore how they are "materialized in practice." Specifically, they explained the important distinction between performance (which refers to the doing of an activity) and performativity (which refers to the outcomes of the doings), a distinction which is also highly relevant in the aforementioned routine dynamics research in which performativity (e.g., the effect of an artifact on routines) is not the same as the performative aspect (the enactment of a routine in a specific place and time, e.g., Feldman & Pentland, 2003).

Also building on the notion of performativity is the work of Introna (2011), which captures how increasingly delegating our everyday life to digital codes is—often subtly and invisibly—shaping human endeavors. While the effects of this encoding of our daily activities into software and algorithms are highly performative, they are also often hidden from sight, too complex and obscure to be visible and traceable to specific agencies. “Design decisions,” he argued, “encoded and encapsulated in complex nests of logical statements—rules within rules within rules—enact our supposed agency based on complex relational conditions, which after many iterations of ‘bug fixing’ and ‘tweaking’ even the programmers no longer understand” (Introna, 2011, p. 115). The implication of this for scholars is the need to appreciate how multiple and intersecting encoded agencies might be translated (and therefore transformed) into multiple and emergent performative outcomes.

Finally, also building on the notion of performativity, Faraj et al. (2018, p. 68) emphasized the need to capture technology’s “highly performative effects,” as algorithms can produce similar effects to Weberian bureaucracy by creating an “iron cage, but whose bars are not readily graspable for bending.” This is because, in the case of algorithms, the rules inscribed by designers or evolved by the algorithm itself “are unavailable for public scrutiny” (Faraj et al., 2018, p. 63). Algorithms, in conjunction with their broader organizational contexts, play a performative role and consequently profoundly influence work and organizational realities (Pachidi, Berends, Faraj, & Huysman, forthcoming). As algorithms increasingly enable modification and control of human behavior (Zuboff, 2015), the agencies that do the modifying become increasingly hidden, a fundamental issue that algorithm researchers need to address.

USING PERFORMATIVITY TO UNDERSTAND ALGORITHMS: THE CASE OF THE CREDIT SCORE

To illustrate how performativity can be usefully invoked to study algorithms, let us consider a credit scoring application described by a credit industry consultant (Big Data Scoring) and represented in Figure 1.

----- Insert Figure 1 about here -----

In this algorithmic assemblage, a consumer applies for a loan, providing information in an application form. Information provided in the application is supplemented by the financial institution's own data, the three major credit bureaus (Equifax, Experian, TransUnion), and data provided by Big Data Scoring. An algorithm (i.e., the "Decision Hub") then takes these inputs and generates a credit decision. Below, we consider in more detail some of the key features of this algorithm-enabled process and illustrate how it can be analyzed through the performativity lens.

Using Theories to Automate Decisions

In the credit scoring case above, the algorithmic assemblage is intended to make a decision about whether or not to issue credit to a particular applicant. This credit decision is enacted with the purpose of achieving a goal, which can be conceptualized at different levels. At a high level, a finance company might have a goal of using a credit scoring algorithm to make more money. Practically speaking, however, an algorithm requires the construction of a tangible and quantifiable goal that can be measured. For example, the algorithmic goal for a credit scoring algorithmic assemblage might be to maximize the sum of the expected profit from a client, less the costs associated with the probability of a default. Generating this type of goal often involves constructing a quantifiable metric that might privilege a certain type of outcome that can be measured; likewise, a quantifiable metric might prevent other incommensurable outcomes from being considered (Espeland & Stevens, 1998). Algorithms may use different techniques to evaluate different outcomes: an algorithmic computational procedure might optimize a particular course of action or allow for a satisficing outcome for the sake of computational efficiency (Simon, 1970).

Closely associated with the decision and the goal is the performative notion of *theory*, an "analytical system that link[s] different concepts in order to explain or predict empirical phenomena" (Marti & Gond, 2018, p. 489). Theories are what algorithms implicitly or explicitly rely on to take a course of action that can yield a desired goal. For example, a credit scoring algorithm predicts the risk that an individual consumer might default on a loan. To generate such a score, individual consumers need to be classified based on a set of attributes that might predict the payment or non-payment of a debt (Lauer, 2017). The attributes analyzed by an algorithm might either be deductively constructed in terms of a theory of debt default, such as the notion that an individual's network of social relations is a determinant of creditworthiness (Hvistendahl, 2017), or inductively derived based on historical experience through machine learning algorithms (Glaser, Krikorian Atkinson, & Fiss, 2020).

Understanding the theory undergirding an algorithm is particularly important, as Kiviat (2019) showed, because the theories used to predict future loss might lead to the generation of morally questionable decisions that reinforce historical patterns of bias and discrimination. Such theories undergirding algorithms can feature differing degrees of formality, ranging from folk theories (e.g., theories that emerge and evolve in the ongoing work of practitioners; see Rip, 2006) to sophisticated mathematical models (e.g., basing patrol decisions on Bayesian-Stackleberg game theoretic models or "random walk" financial models).

Applying theories to instruct organizational activities requires their abstract steps to be materialized in some way. One way an algorithm can be materialized is through a standard operating procedure, which provides general instructions that govern actions by formally representing a routine (D'Adderio, 2003, 2008) or standard, such as ISO 9000 (e.g., Lazaric & Denis, 2005); another way an algorithm can be materialized is through automated recommendations such as those generated by Netflix based on a user's viewing history (Siegel, 2013), and prescriptions for action such as those generated by formulas in an Excel spreadsheet (e.g., Cacciatori, 2003; Glaser, 2017). An algorithm thus can play very different roles in shaping organizational activities such as practices and routines based on their power, or extent of autonomy (D'Adderio, 2008). For example, we might expect rule-based algorithms to feature at the weaker end of the performativity spectrum (as their effects are more visible and easily influenced by human actors), but learning algorithms (such as deep learning) to feature towards the stronger end due to their opacity and capacity to self-generate goals and rules. Overall, an algorithm's computational procedure inherently revolves around decisions, goals, and theories—core concepts that are foundational to the algorithmic assemblage.

Enacting Roles and Expertise

Another feature of an algorithmic assemblage concerns how algorithms enact and transform the roles and expertise of human actors. Different groups, functions, or teams may be involved in determining how artifacts such as algorithms influence organizational practices or routines and how these are enacted (D'Adderio, 2008, 2014; see also Anthony, 2018). For instance, credit decisions traditionally made by individuals through informal evaluations came to rely on data and decisions made by professional credit managers and/or credit rating agencies (Lauer, 2017, pp. 5–6). The different types of actors involved in the enactment of the algorithm led to potential changes in the types of data analyzed and the practices used by the algorithm (Pasquale, 2015). For instance, credit scoring algorithms may use and weight data differently based on professional roles or other identity markers.

In understanding the role of algorithms in organizations, it is therefore particularly important to track the different actors involved in the design/use process, including experts outside an organization (e.g., a "data scientist" might be required to apply algorithms to large sets of data; see Davenport, 2014), because different actors (or groups of actors) may have different perspectives on the algorithm (D'Adderio, 2001, 2008). Unlike scholars who have exhibited a tendency to dichotomize the responses of actors into "designers" who embrace an algorithm and "users" who resist it (Kellogg et al., 2019), we suggest that the dynamics of support and resistance for algorithms are much more nuanced in practice (Bailey & Barley, 2019; Raisch & Krakowski, in press). For instance, in his study of policing routines, Glaser (2017) found that field officers both supported and resisted the algorithm, and that practices associated with the algorithm's design and deployment into the organizational routine determined the extent of their support or resistance (see also, Brayne, 2017). Similarly, Cameron (2020) showed how ride-sharing drivers exercise autonomy while conducting algorithmic work.

Different actors also play an important role in the use of credit scoring algorithms. For example, different actors may be involved in credit scoring across an algorithm's life span. The data scientists who play a central role in developing a credit scoring algorithm, for instance, may not be involved in the application of that algorithm to organizational routines. The algorithm's underlying model may instead be vetted by different staff members in different operational roles within the business (Siddiqi, 2005). This shows how an increasing number and variety of actors may be involved in the "nested" construction and performance of an algorithm over time and across contexts. In summary, understanding the (variety of) actors involved in an algorithm in different nested assemblages is an important aspect that should play an integral role in developing an understanding of the relationship between an algorithmic assemblage and organizational phenomena.

Performing Sociomaterial Calculations

Many important aspects of organizational activities are influenced by the materiality of the calculative practices of an algorithm and its surroundings. The nature of the data involved in algorithmic calculations can also play a significant role in organizational activities, as software may feature different properties that regulate the ability of data to be updated to reflect changes in the environment. Computer hardware materiality can also play an important role (MacKenzie, Beunza, Millo, & Pardo-Guerra, 2012), as high powered computing capacity might lead to the use of more inductive machine learning applications and require less theoretical preprocessing of data.

Visualization is another important sociomaterial feature, because it renders algorithmic output amenable to theoretical analysis and interpretation. For example, in the context of topic modeling algorithms, Hannigan et al. (2019) showed how the rendering of theoretical artifacts from data and algorithms often benefits from the visualization of analytic output. The role of visualization is evident in the popularity of practitioner software applications such as Tableau or Microsoft’s PowerBI, which not only enable actors to make sense of complex information, but also produce visualizations which can serve as devices to facilitate coordination and conflict in organizations (Pollock & D’Adderio, 2012; Pollock & Williams, 2016).

In the credit scoring context, visualizations have been used to help users identify which features provide the best information to effectively predict the likelihood of a credit default. For example, in a blog sponsored by enterprise resource software provider SAS, Violante (2019) highlighted several important visualizations that could be used in a "credit scorecard dashboard," including graphs depicting "information value by feature" and a "customer groups based on quartile score." These devices enable different actors who use the algorithm to understand the process by which the credit score is generated, and also enable them to integrate the algorithm into the broader credit scoring routine.

In addition to visualizations and other artifacts, practices and routines (Feldman, Pentland, D'Adderio, & Lazaric, 2016) are important calculative features associated with the design and use of algorithmic data. The theories mentioned above may undergird an algorithm, but these theories may be only developed and translated in and through practices so that their effects are always temporary and emergent (D'Adderio & Pollock, 2014, 2020). For example, in a credit scoring algorithm, a possible theory is that too much credit capacity might result in an increased probability of default, leading to a lower credit score. But how does the algorithm analyze credit capacity? Is it the calculation based on total credit limit, or the percentage of the total credit limit owed by an individual at a moment in time, or an average percentage of the total credit limit owed by an individual over a period of time (e.g., a year)? These factors must be modeled and decisions must be made beforehand, as a rationalized calculation cannot be made without these inputs (e.g., Cabantous, Gond, & Johnson-Cramer, 2010). Analyzing this process is fundamental to capturing the actual workings of algorithmic systems, something that is afforded under our performativity approach.

Similarly, practices and routines affect not only how to use the data "downstream" in the credit scoring algorithmic assemblage, as depicted above, but also "upstream" in the nested assemblage through which the data themselves are actually constructed. Here choices must be made about which categories of data exist through devices such as commensuration practices (Espeland & Stevens, 1998), which result in the naturalization of algorithmic categories (Alaimo & Kallinikos, forthcoming) that enable specific individuals to be analyzed much in the same way that mortgages are analyzed to make them a tradable security (Carruthers & Stinchcombe, 1999). The infrastructure underlying algorithmic decisions is often invisible and likely to “sink in” (D’Adderio, 2008, p. 774), hiding the political dynamics integral to the construction of data (Bowker & Star, 2000). In performativity terms, routines enact distributed agencies and support their emergence as distinct actants and identities (Butler, 1990). What are the “techniques” (Rieder, 2017) used to enact them in organizational settings? Research suggests that there are substantial implications associated with the layering of assumptions in data applied from other contexts unreflectively (Leyshon & Thrift, 1999) through mechanisms such as error propagation (Rona-Tas, 2017).

To sum up, our framework suggests that scholars can usefully invoke performativity to capture and theorize fundamental aspects of algorithmic evolution, including: the decisions, goals, and theories embedded in the algorithm; the knowledge, roles, and expertise enacted by various actors, including organizational members; and the sociomaterial calculative devices integral to the algorithmic assemblage. To fully develop the potential of performativity theory to advance our understanding of algorithms and their effects, we propose a new approach which builds on performativity’s affordances, while taking it further by addressing some remaining challenges.

THE BIOGRAPHY OF AN ALGORITHM

The performativity-inspired theorization of algorithms and related phenomena has made substantial progress by moving beyond the notion of algorithms as self-standing tools with fixed identities and properties to begin to unpack their complex and nuanced performative effects. However, two outstanding challenges must be addressed to further advance our understanding of algorithmic technologies and organizing.

First, existing organizational research from a performative perspective has not sufficiently developed an understanding of how multiple different and partially overlapping performations might configure technologies and organizations. In performativity terms, this involves explicitly taking into account the nested and multiple nature of theories and their assemblages (DeLanda, 2016; Deleuze & Guattari, 1987) and how these evolve as they travel. This is particularly important in the case of algorithms, as the "chain of materializations" (DeLanda, 2016; Deleuze & Guattari, 1987) concept clearly illustrates. Building on Mol (2002), recent performativity research has highlighted how objects (artifacts, routines) are more usefully seen as coordinated outcomes of different assemblage enactments at different "locations." Objects—such as atherosclerosis in the case of Mol (2002), routines in the case of D'Adderio and Pollock (2020), or algorithms in our case—and their effects, can therefore be usefully understood as the emergent and constantly challenged outcomes of multiple different and partially overlapping performations.

Second, notwithstanding a few exceptions (see Garud & Gehman, 2019; Garud et al., 2018), scholars have not yet fully engaged with the issue of how temporality may influence performative processes, including processes of an institutional nature (Granqvist & Gustafsson, 2015). Assemblages are fluid "objects" which over time can be associated with different actions, such as defining problems, generating interest, enrolling actors, and mobilizing different compositional elements (Callon, 1986; Latour, 1987). Carton (2020), for instance, showed how theories shape assemblages through distinct mechanisms of appropriating, rearranging, and establishing, which typically unfold over time. How can we address these two fundamental challenges?

Drawing on a performative perspective, Williams and Pollock (2011) highlighted the importance of considering the relational, temporal, and contextual aspects of practices when studying digital artifacts such as enterprise software. Building on Pollock and Williams's (2009) study of the history of enterprise resource planning (ERP) software, they analyzed how the configurations of a leading ERP system developed by a major software producer shifted over the course of three decades. Their core finding was that technological artifacts typically take shape as they are enacted across different temporalities and localities (Hyysalo et al., 2019). Given that their "careers" typically extend beyond what can be studied at a single site or moment of technology design or implementation, the authors sketched out a "biographical" approach. Constructing a biographical study was not simply an attempt to capture the "full range of actors and factors involved," which they argued was not "feasible let alone desirable" (Hyysalo et al., 2019, p. 16). Rather, they advocated making choices about which "black boxes to open for detailed examination and … which are to be left unexplored" (Hyysalo et al., 2019, p. 16). Scholars may subsequently "knit together" different moments from the past, in which actors built upon "puzzles and gaps" in existing knowledge, and the present, in which actors are capturing new issues that "unfold from [the current] work" (Hyysalo et al., 2019, p. 9).

To overcome the limitations of the computational tool perspective, we therefore start from the observation that an algorithmic assemblage should be studied as it evolves across contexts and over time. To do this, we develop a biography of an algorithm where we select and study specific "moments" that we see as key in its evolution. Below, we identify the three particularly significant or critical moments which—while not exhaustive—are likely to strongly influence the development of an algorithm and its organizational effects. We envisage that others may choose different moments to study which may be more meaningful to them in relation to particular technologies and/or specific contexts of analysis.

The first moment, *addressing and resolving performative struggles*, captures the competition and conflict among the different algorithmic assemblages attempting to shape practices and organizations. The second moment, *inscribing and layering programs of action*, focuses on efforts to create or enroll an algorithm and to configure it to enact new practices or organizations. The third moment, *translating an algorithm to other contexts*, refers to how algorithms travel from one context to another. We summarize these moments in Table 1 below.

----- Insert Table 1 about here -----

We develop the concept of biographical moments by applying it to the scoring algorithm introduced and discussed above. As elaborated earlier, a credit score is used to determine an individual's likelihood of default in the credit market (Kiviat, 2019) or in market transactions more generally (e.g., Fourcade & Healy, 2017). A typical credit scoring algorithm uses a series of inputs to construct a credit score that reflects the probability that an individual will default on a debt (Poon, 2009). An organization can use either heuristics or experience-based segmentation that relies on past understanding of credit data to leverage mathematical algorithms to generate a credit score (Siddiqi, 2005). For example, in developing an experience-based model, an organization might use an algorithm that constructs a credit score using organization-defined weights of demographic characteristics (e.g., income, employment status, etc.) and behavioral characteristics (e.g., payment history, outstanding debt, etc.) (Siddiqi, 2005, p. 109ff). Alternatively, an organization might use more sophisticated algorithms such as decision trees or

K-means clustering to inductively derive customer segments that can feature distinct credit scores.

Moment #1: Addressing and Resolving Performative Struggles

A first important biographical moment involves addressing and resolving performative struggles. This moment captures a critical spatio-temporal juncture where assemblages are being contested within or beyond an organizational context. Controversies around algorithms may arise, for example, when assemblages undergo substantive change, or when new assemblages emerge. We highlight three performative struggles that are particularly important when it comes to algorithmic assemblages: the introduction of an algorithm to replace a more traditional technology (algorithmic vs. non-algorithmic assemblage); the deployment of different configurations of the same algorithm (same algorithm, different assemblages); and conflicts between/among different technologies (different algorithmic assemblages).

First, controversies may emerge when an algorithm is first introduced to replace more traditional technology. We theorize this as a conflict between algorithmic and non-algorithmic applications of the same technology/solution. For instance, prior to the now-commonplace use of credit scoring algorithms, issuing credit was almost entirely an informal process whereby merchants drew upon direct knowledge of their local customers' personal circumstances and trustworthiness to decide how far they were willing to let each run into debt (Lauer, 2017). In so doing, credit managers viewed the customer's "character" as being more important than other factors such as "capital" or "capacity." They subsequently contributed to configuring the new technology, which relied on credit scorecards, towards the goal of "augmenting" the power of the credit manager in making character judgments about their customers, rather than as a means of automating human intelligence, thereby fundamentally influencing the intial shape of the credit scoring algorithm and its assemblage.

Second, conflict can arise when the same algorithm is deployed in different local configurations bearing different user implications. We theorize this as tensions between different applications of the same algorithm. In the Big Data credit scoring process described earlier, for example, the algorithmic decision hub might feature an algorithm that could be deployed in two different configurations: the algorithm could return a decision that automatically adjudicates the credit application, or the algorithm could provide a recommendation for an organizational member that could be overridden. This is an important difference, because the credit scoring algorithm's influence on the ability of individuals to override the recommendation may generate tensions at the implementation stage, depending on the perceived fit with existing activities. For example, in their study of the introduction of credit cards to consumers in post-communist countries, Guseva and Rona-Tas (2014) showed how unique actions and activities in different nations constructed a market that facilitated the use of credit scores, leading to a different degree of adoption; in some nations, such as Russia, Ukraine, and Bulgaria, uptake remains limited. The issue of local deployment also connects with recent management research. For instance, Newman, Fast, and Harmon (forthcoming) showed how the practices used to incorporate algorithms into organizational decision-making have significant impacts on how employees perceive procedural justice, resulting in tensions which vary in intensity depending on local perceptions.

Third and finally, struggles may emerge as different algorithmic technologies replace each other over time. We theorize these as competitions between different types of assemblages. Poon (2007), for example, documented how Fair, Isaac & Company developed different algorithmic technologies to calculate credit scores at different points in time. Early technology featured custom scoring applications for companies, many of which were in rural locations. The credit scoring assemblage in this case allowed a clerk—often an individual with minimal statistical abilities and training—to be able to gather information from a loan application and compare it to a table to determine a credit score. This initial algorithmic configuration enabled different clients to develop customized credit scoring practices.

This initial assemblage was later replaced by the "prescore" (Poon, 2007), which enabled companies to proactively offer credit based on a predefined review of individuals—in turn allowing them to contact potential consumers with unsolicited marketing offers for credit cards. This created tensions by shifting the power balance between lenders and borrowers, with the former initating the economic transaction surrounding consumer credit and holding an advantage based on information (Poon, 2007). This new technology configuration or assemblage eventually displaced the customized score, as Fair, Isaac & Company began to market it as a generic product. A similar change occurred when the company shifted from using this prescore assemblage to the FICO score that is currently used.

Moment #2: Inscribing and Layering Programs of Action

A second key biographical moment captures the progressive sedimentation of assumptions within an algorithmic technology throughout the course of its lifecycle. We theorize this through the notion of "inscribing and layering of programs of action." Capturing and theorizing this moment requires scholars to understand not only how particular actors (e.g., algorithm designers) come to be motivated to construct an analytic problem to be addressed through an algorithm, but also how conceptions of such problems may shift over time (Pachidi, 2015; Steele, 2016). The biographical approach, for example, highlights how the design of workplace technology is often based on explicit theorizations about the general characteristics and implications of technologies for contemporary organizing. Thus, algorithms may be designed according to an "imagined future" (Neyland, 2015, p. 125) or may draw upon "metaphors" (Totaro & Ninno, 2014, p. 41) about these general characteristics and implications, as well as "visions" about how organizations could be transformed by algorithms deployed in organizational activities. Often, these visions of future offerings are driven or informed by the perspectives of suppliers, bringing together technical potentials and expectations of organizational efficiency and performance. For instance, Neyland (2015) characterized algorithms as revolving around a multi-part vision of the role of automation within an organization, which involves partially or progressively moving away from manual tasks or tasks involving human decision-making towards the automation of such processes.

Another example of layering as a core biographical moment is how designers develop a model of the anticipated user and how the artifact could—or should—be used. This effort intrinsically requires the construction of a projected future (Bucher, 2017; Wenzel, Krämer, Koch, & Reckwitz, 2020), a notion drawing on Simon's (1970) "sciences of the artificial." Alongside the "technical" procedures within an algorithm, designers develop a conception about potential uses, users, and broader use scenarios. Akrich (1992, p. 208) aptly described how designers inscribe preferred "scripts" or "programs of action" within technological systems: "A large part of the work of innovators is that of 'inscribing' this vision of (or prediction about) [potential uses and users] in the technical content of the new object." Such ideas have been used to show how technological design can favor the interests of particular actors over others. Similarly, in their study of algorithms within the eBay platform, Curchod et al. (2020, p. 667) showed how programs of action empower some groups of actors by granting them more rights (e.g., buyers evaluating sellers) while disempowering others (sellers cannot reciprocate with negative evaluations), and by establishing procedures that regulate interactions on the platform (e.g., by imposing evaluation criteria on buyers or downgrading sellers with low scores).

Although such models and choices are often explicit, they also can be implicit (Faraj et al., 2018). For instance, employing what Oudshoorn and Pinch (2005, p. L450) described as "I-methodologies," designers may draw on their own knowledge or previous experiences and incorporate personal preferences and presumptions into algorithms. In the case of a credit scoring algorithm, this might be an implicit theory (e.g., that people with substantial outstanding credit are more likely to default on their loans). Such constructions may be informed by anecdotes or stereotypes, but also may incorporate other relevant evidence or experiences of the problem rooted in other markets. For instance, in China, financial institutions with government backing assess creditworthiness based on an individual's associates (Hvistendahl, 2017), and financial institutions in the United States are increasingly using data from social media to model individual creditworthiness (Siddiqi, 2005).

Finally, another important example of inscribing and layering programs of action involves developing representations of the environment. Simon (1970) explained how actors creating artifacts such as algorithms must develop representations of the environment, and then create an evaluative process to adjudicate proactively between preferred outcomes. This requires constructing a rational process (Cabantous & Gond, 2011); although it may eventually become taken for granted and embedded in an algorithm, this process must be developed through actions that involve contextualization, quantification, and calculation (Cabantous et al., 2010). For instance, Glaser (2014) showed how organizational members must actively model and map environmental conditions into numerical parameters that can be evaluated by the algorithm: law enforcement officials must abstractly represent the capacities of different types of patrols (e.g., How does an algorithm differentiate between an undercover officer and an officer with an assault rifle?) and the values of specific geographic locations. Understanding the practices associated with the representation of the environment and the evaluation of different potential outcomes is thus an extremely important part of the biography of an algorithm.

Moment #3: Translating Algorithms to Other Contexts

The moment of an algorithm's translation (Callon, 1986) to another context is becoming increasingly important due to the prevailing assumption that an algorithm designed for one setting can be recycled across similar classes of organizations, similar or related industrial sectors, or even different and unrelated sectors and organizational forms. For instance, Rona-Tas (2017) studied how credit scoring algorithms have been progressively extended beyond their original use context into "fields such as auto insurance assessments, cell phone contracts, residential rentals, and even hiring decisions" (p. 52). While the original credit scoring algorithms were written from scratch to address a particular organizational problem, the code and functionality were applied to other areas to address new issues in contexts where users had different motivations and interests.

In this sense, algorithmic systems form part of an established practice in the supply of software systems, whereby suppliers recycle the same systems in different areas (Pollock & Williams, 2009). They can do this, suppliers argue, because such solutions are fundamentally based on the notion or theory that organizations comprise "common" elements (Totaro & Ninno, 2014, p. 35). When transferring algorithms, the "generic-ness" of such solutions is viewed as a feature, not a flaw. Many key industry players have already signaled a vision of the "algorithmic marketplace" (Gartner, 2016), predicting that algorithmic standards will be created and that algorithms will not be built anew, but reused across organizations. Thus, it may be fruitful to investigate how algorithms "travel" from one organization, industrial sector, or country to another: the application and use of a "commodified" algorithm in a new setting constitutes a particularly important (but also highly contested) moment in its biography, and thus would be important to study.

Translation is an instance of analogical transfer (Cornelissen & Clarke, 2010) that involves the transfer of a concept, idea, or practice from one domain to another. The notion of translation suggests that transfer always involves transformation (Czarniawska & Sevón, 1996, 2005; Latour, 1987) and recreation (D'Adderio, 2014; D'Adderio & Pollock, 2020). Translating an algorithm from one location to another, for example, may create inspiration for new ways of doing things. For instance, Glaser, Fiss, and Kennedy (2016) showed how translating financial market algorithms for the online advertising industry involves fundamentally transforming the processes of buying and selling display advertisements through mechanisms of stretching, bending, and positioning. This suggests that the practices by which algorithms are transferred between domains fundamentally reshape the assemblages. Translation is never a simple and clean process.

Translating an algorithm's underlying assumptions from one context to another, however, might end up creating problems. Rona-Tas (2017), for example, described how "credit ratings may be used in new ways outside the context of credit granting" (p. 53). This includes using the ratings to inform decisions about car insurance, home rentals, and hiring, resulting in what he termed "enhanced performativity" (p. 57)—where the "theory" underlying an algorithm not only assesses, but actively influences the creditworthiness of individuals. It also includes "turbo performativity" (p. 68)—whereby scoring algorithms draw on "theories" from similar scoring technologies in other contexts to provide a composite score of the individual, potentially causing errors in a nested assemblage that end up propagating to other contexts. Similarly, Brayne (2017) revealed how financial credit scoring methods and algorithms—including "predictive analytics" and "risk models"—have been applied in the policing context, reconfiguring understandings of policing practices, and provoking a shift from reactive to proactive policing (see also Martin, 2019, for a similar application of scoring algorithms in parole decision-making).

Synopsis: Potential Applications of the Biographical Moments Framework

The biographical framework sketched here can be invoked to unpack and analyze the various ways in which an algorithm and its assemblage(s) are enacted within and across different moments. For example, the *translating an algorithm to other contexts* moment might involve analyzing the process whereby a novel application of an algorithm is first formulated and envisioned. A range of actors may become enrolled in the performation, including policymakers, academics, industry analysts, and entrepreneurs engaged in constructing a vision for the algorithm and its future use, in addition to the mathematical modelers who conceive and articulate the initial formula. A range of artifacts and material features might be created or invoked, including policy documents, norms, standards, and regulations, mathematical symbols and equations, the minds and bodies of mathematicians and logicians, etc. A number of practices might be performed as part of this process, including policy-making practices such as meetings dedicated to establishing the algorithm's ethical and legal framework (aimed, for example, at protecting societal values such as privacy, fairness, equality, and transparency), the problem-solving practices and routines of mathematicians, etc. Various theories and narratives might be drawn upon to construct the algorithm, including mathematical theories or policy goals and related assumptions.

Similarly, the *inscribing and layering programs of action* moment might focus on the key processes whereby an initial algorithmic code is developed into a fully-fledged technology. Here, we might find actors such as data scientists and informaticians who translate vision-embued mathematical formulas into software scripts or lines of code; policymakers and analysts who might be involved in selecting from among contrasting designs based on different ethical and legal considerations; and entrepreneurs and companies which may advocate one design solution over another (e.g., open vs. closed designs). Artifacts invoked at this stage might include the standards underpinning the algorithm's ethical and legal framework, industry analysts' hype cycles which identify future technological trajectories, etc. Practices may emerge, including those enacting the (often distributed) design process (e.g., workshops, hackathons, entrepreneurial challenges, etc.) and new business models (e.g., business model canvas building and scenario planning workshops). Relevant theories might contribute to the process in the form of ethical principles and norms, as well as innovation theories based on technological trajectories.

The *addressing and resolving performative struggles* moment might, for example, capture the process of adopting and adapting a technology to a specific setting. This might involve the business organizations and workforce tasked with the local implementation of an algorithmic system, public organizations such as trade unions supporting or contesting the adoption of technologies (e.g., based on their perceived skilling/deskilling or job creating/destroying potential), etc. Artifacts might be invoked, including adoption evaluations, implementation plans, and procedures (e.g., stage-gate flowcharts), and budget spreadsheets. A number of practices might be enacted, including change management workshops, union meetings and briefings, and operational meetings. In addition, a number of managerial strategies (such as total quality management or lean production) and public management directives may be inscribed and invoked, thereby shaping the algorithm by acting as performative theories.

As the algorithm emerges over time and travels across space, we can therefore expect a progressive stratification of theories and logics (as both complementary and conflicting logics become embedded in the algorithm); the progressive honing of the algorithm through its involvement in performative struggles amongst various organizational agencies; the emergence of algorithm supporting practices and routines; and the reconfiguration of algorithms and their assemblages as they are re-created at other sites. Importantly, the algorithm's biography may also be marked by a series of unpredictable interactions. For example, failed adoptions may lead to an algorithm's reformulation; a transfer issue may lead to its reconstruction; and designers may choose adopt and reuse an existing algorithm rather than start from scratch. Thus, we can potentially have "recycled biographies" where the initial key moment becomes a design process that involves reusing a history-laden algorithm; "reverse biographies" where unsuccessful translation triggers the redesign of an algorithm; "truncated biographies" where one algorithmic technology, having failed within an organizational setting, is replaced by another; and "accelerated biographies" where actors jump directly from one moment to another. Multiple possibilities and configurations can be captured by our biographic framework.

DISCUSSION

The biography of an algorithm framework introduced here may be of relevance for scholars of management and organizations across a number of topics and debates. For the sake of this paper, we focus on three key theoretical conversations which we deem especially meaningful in relation to algorithms: (a) organizational decision-making, (b) the spread of theories and technologies and their logics, and (c) the dynamics of practices and routines. We now describe each of these opportunities in detail.

Understanding Algorithms and Organizational Decision-Making

A recent topic of debate in the academic literature pertains to the decisive influence of algorithms in organizational decision-making. The first position builds on early organization theory to show how algorithms can help decision makers overcome some of the limitations to rational decision-making, including bounded rationality—that is, actors' tendency to compensate for limitations associated with time, information availability, and information processing capacity by opting for satisfactory, rather than optimal choices (March, 1978; Simon, 1947). Specifically, algorithms can help organizational actors overcome biases in decision-making by facilitating a quantitative, evidence-based approach that relies on data and mathematical evaluation of alternatives rather than human intuition (Davenport & Harris, 2007).

In contrast, the second position in the decision-making debate suggests that algorithms may actually introduce additional bias into decision-making processes. One basis for this critique is that powerful actors may simply use algorithms to embed their interests in decision-making processes at the expense of less powerful actors (Kellogg et al., 2019). Another is that algorithmic analysis relies on data that may include errors, and may actually magnify bias (Rona-Tas, 2017).

Both of these perspectives provide interesting insights into the influence of algorithms in organizational decision-making, but offer contradictory interpretations and explanations of similar phenomena. This reaffirms the need for analytical frameworks that can capture the different effects of algorithms and how these effects can be analyzed over different time spans. In relation to the varying effects of algorithms, for example, Newman et al. (forthcoming) found a link between an individual's perception of algorithmic decision-making and the perceived fairness of decisions. Interestingly, their research shows that individuals may react negatively to algorithmic decision-making because algorithms inherently stimulate processes of quantification and decontextualization in ways that cause individuals to question the fairness of algorithms. The algorithms' effects, in this case, appear to be moderated by human control or discretion over algorithmic decisions.

This suggests not only that technologies are patterned by shifting perceptions in fairness in decision-making, but also that the broader trust humans have in algorithms is not stable (Glikson & Woolley, 2020) and is constantly evolving (for some recent empirical explorations, see Jago, 2017; Schafheitle et al., 2020). For instance, the perception of bias in algorithmic decision-making may be weak during the initial introduction of an algorithmic technology, but may become stronger as the system is used (or vice versa). In this context, the biographical approach suggests that we need to pay as much attention to the immediate implications of algorithmic technologies as we do to their longer term evolution as they become entangled within organizational practices.

Understanding Algorithms and the Spread of Technologies and Their Logics

Work related to institutional perspectives, another important strand of organization theory, has focused on how theory triggers organizational change and wider economic and societal transformation (e.g., Ferraro et al., 2005; Marti & Gond, 2018; Strang & Meyer, 1993). Recently, scholars have suggested that institutional perspectives are particularly relevant for studying the spread of technological phenomena (Hinings, Gegenhuber, & Greenwood, 2018). For example, reflecting on the transformational aspects of digital and algorithmic platforms, Hinings et al. (2018, p. 54) wrote that the "creators of digital infrastructures seek to infuse their norms, values, or institutional logics into the infrastructure," thereby shaping what is taken-for-granted (Harmon, Green, & Goodnight, 2015; Steele, in press).

Studying the diffusion of digital infrastructures thus becomes a case of analyzing how institutional logics and related broader "theories" may be embedded in infrastructures and subsequently adopted. Institutional scholars start from the premise that digital technologies are adopted as a result of isomorphic pressures due to the influence of prevalent managerial, technological, or industrial standards (Shoib & Nandhakumar, 2009). Digital and algorithmic platforms, in this view, are often seen as successful because they are composed of already legitimate "building blocks" (Hinings et al., 2018). Building blocks are "generally-accepted, ready-made or customizable modules"—like ERP systems, credit scoring systems, the AppStore, and Slack—which are combined and incorporated into new digital infrastructures. Such building blocks come with built-in "value-laden designs," as in the case of ERP systems, which are based on "the logic of managerial rationalism" (Hinings et al., 2018, p. 55). However, institutional approaches have not yet yielded tools to trace these kinds of extensions, leaving underspecified how such blocks already comprise codified and programmed representations of organizational theories and logics, how these may become embedded in technologies, and how they might apply and fit into new organizational settings.

The biography of an algorithm framework might therefore complement institutional approaches in theorizing the spread of technologies and their embedded logics (for a similar complementary perspective, see the actor network theoretical approach of Sage, Vitry, & Dainty, 2020). For example, in describing the creation and evolution of digital building blocks, Hinings et al. (2018) seemed to suggest the need for an analytical shift from studying technologies as discrete and isolated to a perspective that explores their evolution and development as they become part of larger platforms and infrastructures. This resonates with the biography framework's concept that digital technologies (including algorithms and their codes) are often not built anew, but recycled across contexts. As part of the process of diffusion, their embedded "histories" (including logics, assumptions, and rationales) are transported to new locales where they potentially transform adopting organizations (Williams & Pollock, 2011). Interestingly, our framework suggests that the extension of such technologies is beset by struggles, frequent setbacks, and in some cases, full reversals, as gulfs and schisms between the various organizational presumptions embedded in algorithms and the structures and practices of adopting organizations come to the fore (Pollock & Williams, 2009).

Understanding Algorithms and the Dynamics of Practices and Routines

Finally, our biography of an algorithm framework offers the potential to advance understandings of another core organizational phenomenon: organizational practices and routines. Our biography of an algorithm approach builds on recent contributions in routine dynamics to provide a framework for understanding the deeper and emergent dynamics through which algorithms are implicated in—and perform—practices and routines. In contrast with earlier work, in which scholars have theorized technology and artifacts as isolated, passive tools adopted at the discretion of routine participants (see D'Adderio, 2011 for a discussion), we see algorithms as constituted in wider agentic sociomaterial assemblages whose relational properties evolve and shift as they are re-enacted, with varying degrees of performativity (D'Adderio, 2008; MacKenzie, 2006; Power, in press) across contexts and over time. Recent developments in routine dynamics, as informed by performativity theory, are therefore providing fertile ground for a future agenda aimed at capturing the co-production of algorithms and organizational practices and routines, and their consequences for organizations. We describe potential advances along two main dimensions.

First, our emphasis on emergence and relationality suggests the need for scholars to move beyond the idea of routine embeddedness (Howard-Grenville, 2005, see D'Adderio, forthcoming for a critique) which implies a sharp separation between routines and their (in this case artifactual) context. Rather than considering routines and algorithms as separate entities which interact, we can gain new insights by examining the practices/routines which enact different versions of the same algorithm across different organizational contexts and over time. Building on D'Adderio and Pollock (2014, 2020) for example, we can trace how specific sociomaterial configurations of practices/routines and algorithms emerge and evolve as they move across settings and over the course of an algorithm's biography. In so doing, we can capture how an algorithm's properties might emerge from the coordination of multiple versions of the algorithm as enacted across different sites and over time.

Second, our biographical approach helps break down another kind of artificial separation often present in the routines literature between routines and organizational and institutional levels. It does so by highlighting how algorithms, as multi-faceted artifacts encoding a range of institutional and organizational rules, norms, principles, goals, etc. (theories, in performativity terms) (D'Adderio, 2008; D'Adderio & Pollock, 2014; Glaser, 2017) fundamentally shape the practices and routines that enact (design, transfer, implement) them. As bearers of histories and makers of futures, algorithms can thus provide vantage points from which to observe and theorize how institutions (norms, cultures, professions) shape routines through being embedded in artifacts. For example, principles of democracy and openness can be encoded in algorithms at the design stage, which will subsequently shape the ability of users downstream to access or modify an algorithmic platform. This approach may also help theorize how algorithm-endowed routines may in turn shape institutions. For example, an algorithmic performation at a specific time and/or in a specific context may uncover errors or biases embedded at the design stage, thereby prompting algorithm redesign.

CONCLUSION

In this paper, we have addressed the important, emergent phenomenon of algorithmic organizing. As is clearly evident from our analysis, this is a timely issue that merits urgent scholarly attention, as it holds fundamental implications for organizations and organizing. In assessing some of the contributions and limitations of the extant literature, we have highlighted how a new approach based on the biography of an algorithm holds potential to provide a deeper and more nuanced understanding of the effects of algorithms on organizations, while also helping to advance several central themes in organization theory. In so doing, we hope we have established a theoretically-grounded, methodologically-novel, and empirically-relevant scholarly agenda which addresses the far-reaching, contemporary issue of algorithmic technologies and their roles and impacts on the economy, organizations, and society in all of its multifaceted complexity.

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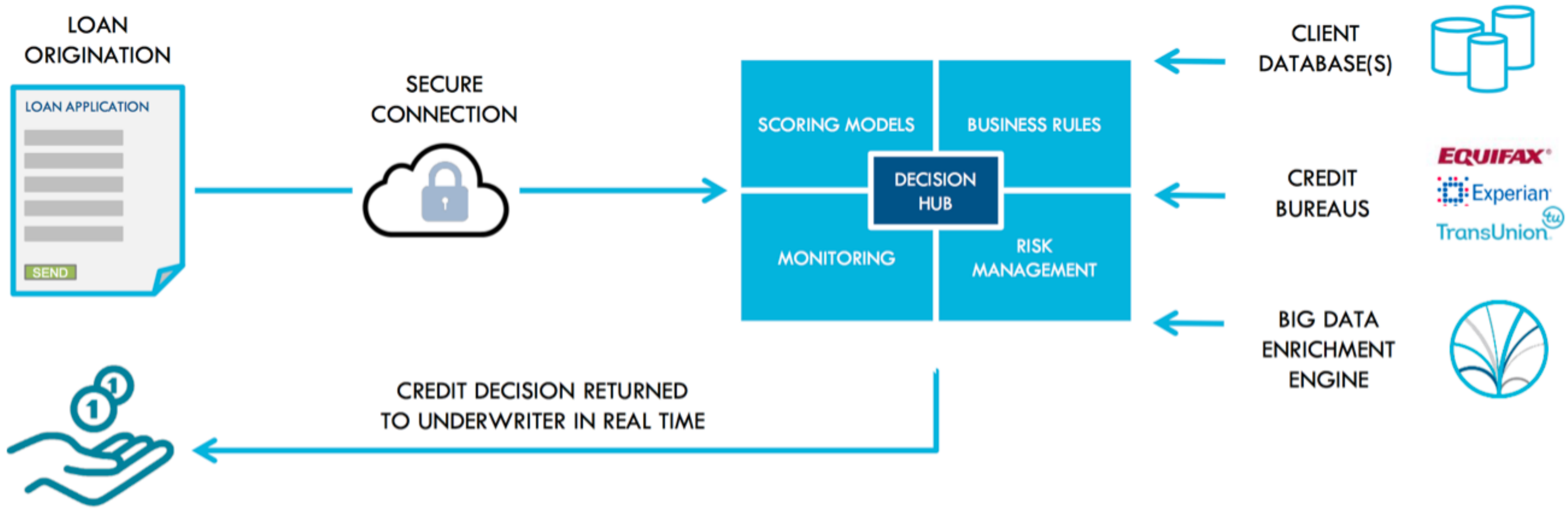
TABLE 1: ***The Biography of an Algorithm***

Biographical moment	Definition	Analytic focus
Addressing and resolving performative struggles	Conflicts between different algorithmic assemblages attempting to obtain jurisdiction over organizational activity	Scrutinizing conflicts associated with algorithmic assemblages: - An algorithmic assemblage can conflict with a non-algorithmic assemblage - The same algorithm can be deployed in different assemblages - Different algorithmic assemblages can come into conflict
Inscribing and layering programs of action	Efforts to use an algorithm to design a new imagined organizational future	Dissecting the designing actions used to create and deploy an algorithmic assemblage, including: - Envisioning a desired imagined future state - Establishing evaluative mechanisms to differentiate between different future states - Representing an environment in terms of digital parameters
Translating an algorithm to other contexts	Taking an algorithm from one context and applying it to another context	Inspecting the actions stimulated by the relocation of the algorithm, including: - Similarity mapping of outcomes and assumptions - Enrolling stakeholders to support the new assemblage

FIGURE 1: ***Big Data Scoring's Decision Hub***



Source: Big Data Scoring, 2020